Chapter

Electrical Vehicle-Assisted Demand Side Energy Management

Xing Luo, Xu Zhu and Eng Gee Lim

Abstract

The recent development of electrical vehicles (EVs) offers vast benefits not only in environmental protection and economics but also in demand response (DR). Employing EVs in load scheduling enables householders to help alleviate the network load burden while reducing their own electric bills. In this chapter, innovative EV-assisted DR strategies with an EV auxiliary power supply (APS) model and a neighbor energy sharing (NES) model are proposed, to jointly optimize the load distribution for both individual household and multi-household network via vehicle-to-home (V2H) and vehicle-to-neighbor (V2N)connections, respectively. The proposed DR strategies take account of the comprehensive impacts of EV charging behaviors, user preferences, distributed generation, and load priority. The effectiveness of the proposed energy management solutions is verified by numerical results in terms of load balancing and cost reduction. The proposed DR strategies also significantly outperform the previous approaches.

Keywords: electrical vehicle, demand response, energy management, auxiliary power supply, energy sharing

1. Introduction

Among a variety of innovative technologies in the twenty-first century, demand response (DR) has been regarded as a promising long-term solution to improving energy efficiency and reducing energy wastage. It also plays a significant role in both balancing energy supply and demand and enhancing the reliability in smart grid [1–3]. The basic concept of DR management is to reduce or shift the demand for electricity during peak periods in response to dynamic pricing (DP) or other forms of financial incentive, thus achieving the aim of saving electric bills for customers. In other ways, it is also beneficial for power grid as it offers an effective solution to average the power usage in certain periods to alleviate the load burden of the power grid [1–4].

Meanwhile, electric vehicles (EVs) are becoming a trend in the next generation of transportation due to their economic and environmental benefits and the rapid advance of rechargeable battery technology [5–7]. Along with the worldwide application of DP, an increasing adoption of EVs in residences brings about both opportunities and challenges for smart grid. Residences with EVs consume more electricity and react more elastically to electricity price [8]. According to the report provided by the US Energy Information Association [9], the fast charging of an EV is equivalent to about 120 houses coming on line for half an hour, which is a severe issue to the power grid. On the other hand, the usage of EVs as energy storage units via vehicle to home (V2H) offers an effective solution to load shaping at demand side. In addition to this, the surplus energy of EVs can be delivered to neighbor via vehicle to neighbor (V2N) if it is enabled. Hence, householders are able to participate in load scheduling and may have multiple options in energy allocation.

The importance of DR cooperating with EVs increases, since EVs become prevalent recently. Considering the flexible energy storage purpose of EVs, more up-to-date DR strategies that take the behaviors of EVs into account are required. The implementation of DR with EVs requires efficient energy distribution management and high-performance batteries as basis. Moreover, DP provides a basic control signal to optimally schedule the charging and discharging of EVs, by minimizing the overall cost.

Compared with the conventional energy storage system (ESS) and other energy production facilities, the utilization of EV as a temporary power source has advantages in employing flexibility and economic efficiency [10]. It does not expect extra investment besides the daily used EVs. Meanwhile, the power sharing is enabled from the V2N connection. The surplus energy of EVs can be shared to neighbors during peak price time and benefit for both sides. Therefore, the DR strategy with EVs holds wide prospects in practice not only for an individual household but also for the multi-household network.

Much research has been conducted on demand response, and there are many popular DR strategies considering EV impacts being presented in literature. For example, in [11], an optimization framework-based DR program was proposed, with high penetration of EVs and storage systems from residential customer's perspective as well as utility company's perspective. The simulation results showed that the appropriate scheduling has benefits for both customers and suppliers. In [12], authors focused on EVs' charging behaviors based on the collected data from EV charging session, and different types of charging behaviors were derived. Nonetheless, the specific DR program with the proposed charging profiles has not been declared. To analyze the potential usage of EVs in power grid, the optimal time of EVs' charging and discharging was explored in [13]. However, all the mentioned studies above are limited to the operation of a single user and fail to attempt the scheduling of EVs among a group of households in DR program.

Moreover, authors in [14] proposed an algorithm for EVs' scheduling in DR to optimize the peak demand. The optimization problem is studied in a game framework. However, other electric appliances have not been considered in this work. In [15], an intelligent preemptive DR management using a building energy management system was proposed to better schedule the energy consumption within buildings. In this work, dynamic EV charging scheduling, priority-based load shedding, and air-conditioning system were accounted. Authors in [16] presented an optimal behavior of plug-in EV parking lots in the energy and reserve market. Both price-based and incentive-based DR programs were developed, and uncertainties of plug-in EVs were also considered by using the stochastic programming approach. In addition to these, a number of interesting DR programs coordinating with EVs are also described in [17–19].

In this chapter, we propose two innovative EV-assisted DR strategies with an EV auxiliary power supply (EV-APS) model and a neighbor energy sharing (NES) model, to jointly optimize the load distribution for both individual household and multi-household network via vehicle-to-home (V2H) and vehicle-to-neighbor (V2N) connections, respectively. Compared with the previous research, the main contributions of this work are:

1. Two significant EV-assisted DR strategies for domestic appliance scheduling are designed and implemented to different scales of households (individual

household network and multi-household network) in order to alleviate the load burden for the grid and save electric bills for householders, simultaneously.

2. For the individual household network, EV is utilized as an auxiliary power supply (APS) for energy consumption of home appliances on special occasions. An EV-APS model-based DR strategy is proposed.

3. For the multi-household network, an EV-assisted DR strategy including a neighbor energy sharing (NES) model for a residential network with different types of EVs installed at consumers' premise is developed. The surplus EVs' energy distribution is enabled via vehicle-to-home (V2H) and vehicle-to-neighbor (V2N) connections in this chapter. The NES-based DR strategy is valid and effective not only for an independent household but also for a multi-household residential network, which can satisfy broader requirements compared with conventional DR strategies in literature. The energy trading policy in neighborhood is also declared.

4. Comprehensive affecting factors (e.g., EV behaviors, user preferences, load scheduling priorities, etc.) are considered in scheduling for both EV-assisted DR strategies. The effectiveness of the proposed DR strategies is verified by numerical results, which demonstrate that our approaches significantly outperform the methods in literature in terms of load balancing and electricity cost reduction.

2. Electrical vehicle-assisted demand response strategy for individual household

An innovative electrical vehicle (EV)-assisted demand response strategy for load scheduling within an individual household is illustrated in this section. An EV auxiliary power supply (EV-APS) model is presented first. Afterwards, the system models are introduced mathematically. At last, the problem formulation and optimization method are proposed.

2.1 EV-APS demand response network

The schematic diagram of the proposed DR strategy with the EV-APS model is shown in **Figure 1**. Specifically, householders buy electricity from the power grid for the daily usage including EV charging under a dynamic pricing (DP) tariff. Normally, domestic appliances are directly powered by the main power grid. However, as an interim energy storage unit, EV is able to supply power for the household appliances (HAs) in auxiliaries on appropriate occasions, especially in high-price periods. The time of activating EV-APS is dependent on the instructions from the smart controller.

In addition, the smart controller plays the role as a supervisor in the system network. It regulates the energy sources supplying and the operating time of the household appliances based on real-time load information which is received from the smart meter and other signals (e.g., DP, EV status, load priority, etc.).

Moreover, more than 15 types of household appliances will be used generally in domestic homes every day. Considering the operating characteristic of each appliance, it is not necessary to schedule all of them via DR programs. Hence, in accordance with the device operating characteristics, the household appliances can be classified into different scenarios. In this chapter, household appliances are defined and sorted into two main scenarios as follows:

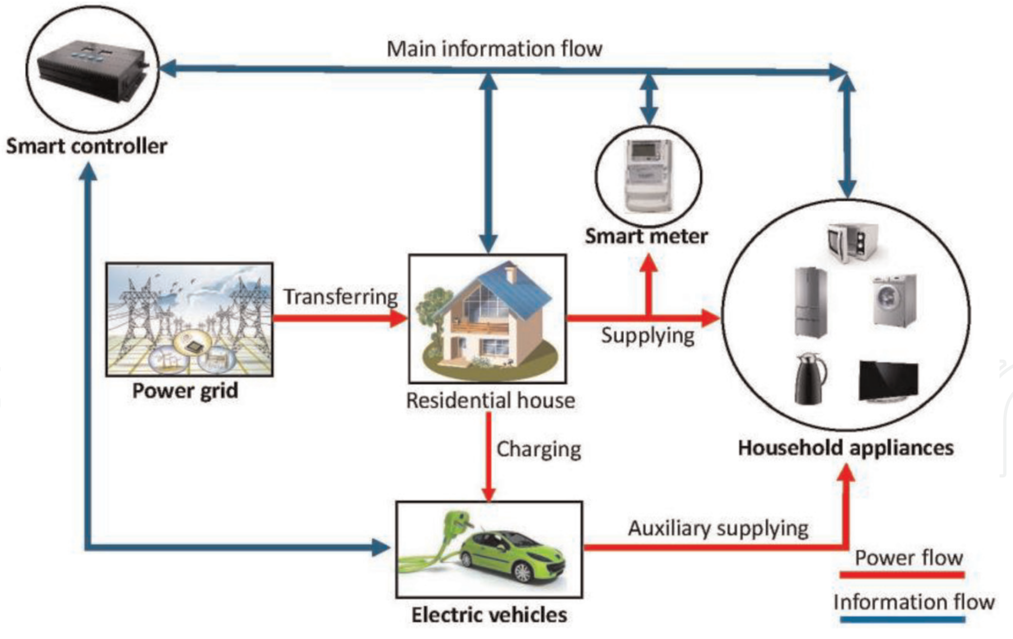


Figure 1.
Schematic diagram of an EV-APS model-based DR strategy for an individual household.

1. Critical scenario (CS): CS contains the appliances that have to be used at a specified time or cannot be scheduled. Examples include lightings, TV, laptop, etc.

2. Flexible scenario (FS): FS contains the appliances that can be powered on with a tolerable delay and have a flexible operating time. Hot water tank and washer are typical representatives in FS.

According to the sorting scheme above, 16 frequently used appliances including EVs are listed and classified with different types of jobs. They can be sorted as follows:

1. CS appliances: refrigerator, water dispenser, toaster, microwave oven, lights, electric cooker, electric kettle, TV, PC, hair drier, and cleaner

2. FS appliances: dish-washing machine, hot water tank, washer, drying machine, and EVs

2.2 System models

In this subsection, the formulation of the EV-APS DR strategy consisting of the main power supply model and auxiliary power supply model is illustrated mathematically.

2.2.1 Main power supply model

First, we define variables W_t^{grid} and P_t^{grid} as the total energy consumption and the total load power on grid at time t, respectively. Afterwards, the main power supply model with the corresponded constraints can be presented as

$$W_t^{\text{grid}} = \int_{T_{\text{in}}}^{T_{\text{term}}} P_t^{\text{grid}} \cdot d(t) \tag{1}$$

$$P_t^{\text{grid}} = P_t^{\text{HA}} + P_t^{\text{EV, c}} - P_t^{\text{EV, d}} \tag{2}$$

$$P_t^{\text{HA}} = \sum_{j=1}^{n} P_{t,j}^{\text{CS}} + \varepsilon_i \cdot \sum_{i=1}^{m} P_{t,i}^{\text{FS}} \tag{3}$$

Subject to

$$\forall t \in [T_{\text{in}}, T_{\text{term}}], P_t^{\text{grid}} \leq P_{\text{max}}^{\text{grid}} \tag{4}$$

$$P_t^{\text{EV, c}} = 0, \text{if} P_t^{\text{EV, d}} > 0 \tag{5}$$

$$P_t^{\text{EV, d}} = 0, \text{if} P_t^{\text{EV, c}} > 0 \tag{6}$$

Equation (1) indicates that the total energy consumption (W_t^{grid}) is equal to the integral of total power (P_t^{grid}) through the time that is between initial time T_{in} and the terminate time T_{term}. Equation (2) illustrates the relationships between the total power and each power-consumed component. Variable P_t^{HA} denotes the load power consumed by the household appliances at time t. Variables $P_t^{\text{EV, c}}$ and $P_t^{\text{EV, d}}$ represent the power rates of the EV charging and discharging, respectively.

Additionally, as it is shown in Eq. (3), P_t^{HA} consists of the power cost by CS appliances ($P_{t,j}^{\text{CS}}$) and FS appliances ($P_{t,i}^{\text{FS}}$), where j and i represent the index of the appliances. The ε parameters have small positive values (e.g., $1{+}e^{-8}$, $1{+}2e^{-8}$, and $1{+}3e^{-8}$) that are determined by assumptions (the total power of appliances is not affected). This setting meets the requirement of having a priority according to user preferences in scheduling FS appliances. The smaller value of ε indicates a higher priority in the scheduling process by DR programs.

In spite of that, $P_{\text{max}}^{\text{grid}}$ is proposed in Eq. (4) as a constraint to limit the maximum power rate on grid at time t for the safety and power distribution considerations. Further, constraints in Eqs. (5) and (6) express that the battery charging and discharging cannot be executed simultaneously; otherwise, the battery will be damaged to a certain extent.

2.2.2 Auxiliary power supply model

Determining the EV-APS model requires sufficient knowledge from previous research. According to the investigation of the current EV market, **Table 1** illustrates the core parameters of five major brands of EVs around the world.

Manufacturer and model	Battery capacity (kWh)	Discharging power (kW)	Driving range per charge (miles)
Tesla, Model S (EV)	60	3.0	273
BYD, Tang 100 (HEV)	23	3.3	63
BMW, i3 (EV/HEV)	33	2.5	114
GM, Chevrolet Bolt (EV)	60	—	283
Nissan, Leaf (EV)	30	—	107

Table 1.
Major brand of EVs in current market.

The parameters include the maximum battery capacity $W^{\mathrm{EV,\,max}}$, the discharging power $P_t^{\mathrm{EV,\,d}}$, and the maximum driving range per full charge.

Moreover, multiple charging schemes are provided for each EV. **Table 2** shows the relevant charging schemes of Tesla Model S which will be used in simulations. It can be seen that the charging power $P_t^{\mathrm{EV,\,c}}$ plays an important role in the grid due to the high power rate of battery charging.

Further, variables $W^{\mathrm{EV,\,(1)}}$ and $W^{\mathrm{EV,\,(2)}}$ are defined as the initial energy storage when people leave home in the morning of the first day and the second day, respectively. Therefore, the EV auxiliary power supply model can be proposed as follows:

$$W^{\mathrm{EV,\,rem}} = W^{\mathrm{EV,\,(1)}} - W^{\mathrm{EV,\,trip}} \tag{7}$$

$$W^{\mathrm{EV,\,trip}} = \frac{D^{\mathrm{trip}}}{D^{\mathrm{max}}} \cdot W^{\mathrm{EV,\,max}} \tag{8}$$

$$W^{\mathrm{EV,\,(2)}} = W^{\mathrm{EV,\,rem}} + W^{\mathrm{EV,\,c}} - W^{\mathrm{EV,\,d}} \tag{9}$$

$$W^{\mathrm{EV,\,c}} = \eta_1 \cdot \int_{T_{\mathrm{c,\,b}}}^{T_{\mathrm{c,\,e}}} P_t^{\mathrm{EV,\,c}} \cdot d(t) \tag{10}$$

$$W^{\mathrm{EV,\,d}} = \eta_2 \cdot \int_{T_{\mathrm{d,\,b}}}^{T_{\mathrm{d,\,e}}} P_t^{\mathrm{EV,\,d}} \cdot d(t) \tag{11}$$

Subject to

$$\forall t,\, W^{\mathrm{EV,\,min}} \le W^{\mathrm{EV,\,rem}} \le W^{\mathrm{EV,\,max}} \tag{12}$$

$$\forall t \in [T_{\mathrm{d,\,b}}, T_{\mathrm{d,\,e}}],\, P_t^{\mathrm{EV,\,d}} \le P^{\mathrm{EV,\,d,\,rated}} \tag{13}$$

$$\varnothing = [T_{\mathrm{c,\,b}}, T_{\mathrm{c,\,e}}] \cap [T_{\mathrm{d,\,b}}, T_{\mathrm{d,\,e}}] \tag{14}$$

Equations (7) and (8) indicate the state relations between the initial EV energy of the first day ($W^{\mathrm{EV,\,(1)}}$), the EV remaining energy ($W^{\mathrm{EV,\,rem}}$), and the energy consumption on the daily trip ($W^{\mathrm{EV,\,trip}}$). In addition, Eq. (9) describes that the remaining energy of EV can be used to cover a portion of energy usage by household appliances via battery discharging ($W^{\mathrm{EV,\,d}}$) and the EV will be charged to an appropriate level for the usage of the second day.

Moreover, Eq. (10) explains the relationship between the total energy charging ($W^{\mathrm{EV,\,c}}$) and the charging power rate ($P_t^{\mathrm{EV,\,c}}$). Parameter η_1 denotes the battery

Charging circuit	Charging power (kW)	Charging speed (miles/hour)	Time cost per 100 miles (hour)
Wall connector (one-phase grid)	7.4	22	4.5
Wall connector (three-phase grid)	11	34	2.9
High-power charger upgrade	16.5	51	2.0
Three-pin domestic adapter	2.3	6.8	14.7

Table 2.
Tesla Model S charging schemes.

charging efficiency. Time parameters $T_{c,b}$ and $T_{c,e}$ represent the begin time and the end time of the charging operation. Meanwhile, the meanings of variables of the battery discharging occasion, which is described in Eq. (11), are similar to those in Eq. (10).

Further, constraint in Eq. (12) presents a limit on the actual amount energy of the EV battery. It cannot drop below the minimum allowed battery capacity ($W^{EV,\min}$) or exceed the maximum allowed battery capacity ($W^{EV,\max}$). Constraint in Eq. (13) limits the actual discharging power rate ($P_t^{EV,d}$) to be less than the rated power of the EV. Additionally, since battery damages will be caused by the simultaneous charging and discharging, constraint in Eq. (14) restricts the operation time of battery charging and discharging.

2.3 Problem formulation and optimization

According to the previous analysis, the problem in this study can be formulated as minimizing the total cost (TC) by scheduling the operating time of the household appliances. Hence, the objective function can be proposed as

$$\text{Min TC} = \int_{T_{\text{in}}}^{T_{\text{term}}} W_t^{\text{grid}} \cdot R_t \cdot d(t) \tag{15}$$

where the variable W_t^{grid} represents the total energy bought from the power grid in time period $[T_{\text{in}}, T_{\text{term}}]$. Additionally, the price variable R_t is time dependent and varies hourly depending on the total load demand [10]. The DP tariff that is used in simulations is given in **Figure 3** in Case study and results section.

In order to obtain the optimal solution and reduce the cost to the minimum, the exhaustive search technique can be used on the basis of the established models. The detail description of the technique is not the focus of this work, so it is not emphasized here.

Note that the remaining EV energy is suggested to be firstly consumed in high-price hours to ensure the maximum electric bill reduction. The feasibility of the proposed EV-APS DR strategy is evaluated in Case 1 in Section 4.

3. Electrical vehicle-assisted demand response strategy for multi-household network

Based on the achievement of Section 2, this section proposes a demand response strategy with multiple EVs for a multi-household network. An EV-assisted DR strategy with a neighbor energy sharing (NES) model is described first. After that, the system models are introduced mathematically in details. At last, the problem formulation and optimization are illustrated.

3.1 EV-APS demand response network

The block diagram of the proposed DR framework with the EV-assisted NES model is shown in **Figure 2**. In this study, it is assumed that each household in the community is registered in the network and controlled by the corresponding automatic control unit (ACU) which plays the role as an instructor of each household. ACU regulates the power supplying and the operating time of the household appliances (HAs, e.g., flexible appliances and critical appliance) based on the dynamic load information which is usually received from smart meters and other request

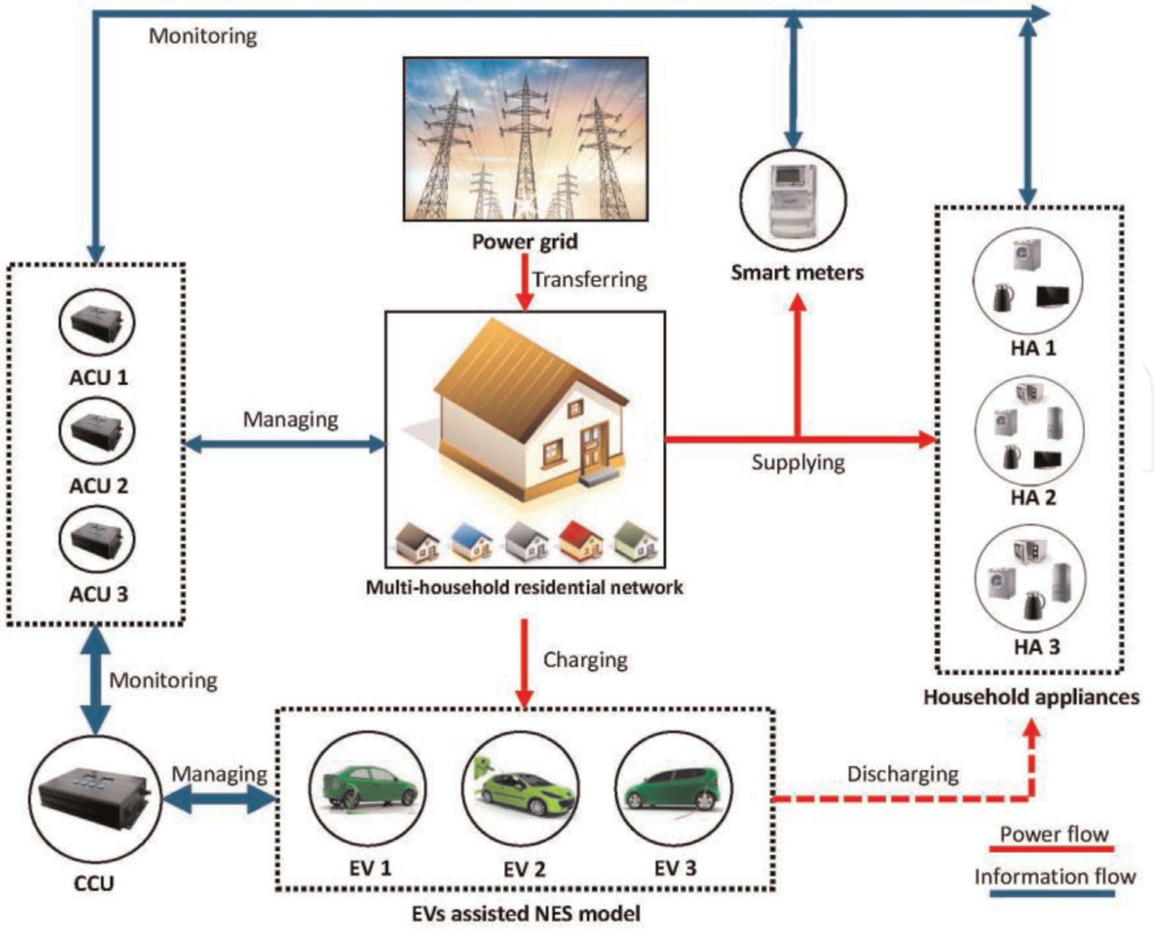


Figure 2.
Schematic diagram of a NES model-based DR strategy for a multi-household network.

signals (e.g., EV status, scheduling priority, DP, etc.). In addition, the centralized control unit (CCU) that is the highest controller in the network globally monitors the status of the ACUs and optimally manages the EV-assisted NES model through the information flows. In the proposed DR framework, customers in the network are registered for two types of connections: V2H connection and V2N connection.

Specifically, the householders buy electricity from the power grid for the daily consumption including HA supplying and EV charging, under the DP tariff. On the one hand, the domestic appliances are directly powered by the public power grid in general. However, the household which is outfitted with EV is able to provide power from EV battery for their HAs on appropriate occasions, such as peak demand periods or power grid outage, via V2H connection. On the other hand, since a limited number of the households are equipped with EV at their premises, the households without energy storage unit may need power assistance from NES model via V2N connection, particularly in high-price periods. When there is surplus energy available being detected in EVs, the CCU determines when and how to allocate the surplus energy to the personal house or the neighbor's houses who have the energy assistance requirements. Generally, the EV energy will satisfy the demand of the EV owner in priority. The energy transaction in neighborhood happens when the power grid is not able to fulfill the demand or the serving load at high charges in peak demand periods. Thus, a customer can receive the power from a neighbor at comparatively lower prices.

The mathematical models of the proposed DR framework will be discussed in the next subsection.

3.2 System models

EVs are utilized as the flexible energy storage units to ensure the energy trading in neighborhood. The following subsections present the mathematical modeling of the system components in details.

3.2.1 Global energy balance model

In order to precisely present the energy transactions between each component in the network with K households, W_t^{grid} and $W_{k,t}^{\text{grid}}$ are defined as the total energy consumption of the entire network and the k^{th} household, respectively, in a time period $[T_{\text{in}}, T_{\text{term}}]$. Afterwards, the global energy model can be proposed as in Eq. (16):

$$W_t^{\text{grid}} = \sum_{k=1}^{K} W_{k,t}^{\text{grid}} \tag{16}$$

where

$$W_{k,t}^{\text{grid}} = \int_{T_{\text{in}}}^{T_{\text{term}}} P_{k,t}^{\text{grid}} \cdot d(t) \tag{17}$$

Moreover, considering the specific power including CS appliances ($P_{k,t}^{\text{CS}}$) and FS appliances ($P_{k,t}^{\text{FS}}$), EV charging ($P_{k,t}^{\text{EV, c}}$), and EV discharging ($P_{k,t}^{\text{EV, d}}$) into the network, $P_{k,t}^{\text{grid}}$ in Eq. (17) can be extended as in Eqs. (18) and (19):

$$P_{k,t}^{\text{grid}} = P_{k,t}^{\text{HA}} + \alpha \cdot \left(\beta \cdot P_{k,t}^{\text{EV, c}} - (1-\beta) \cdot P_{k,t}^{\text{EV, d}}\right) \tag{18}$$

$$P_{k,t}^{\text{HA}} = \sum_{j=1}^{m} P_{k,t,j}^{\text{CS}} + \varepsilon_i \sum_{i=1}^{n} P_{k,t,i}^{\text{FS}} \tag{19}$$

Subject to

$$\forall t,\ P_{k,t}^{\text{grid}} \le P_{k,\max}^{\text{grid}} \tag{20}$$

$$\forall t,\ \sum_{k=1}^{K} P_{k,t}^{\text{grid}} \le P_{\max}^{\text{grid}} \tag{21}$$

Binary parameters α and β in Eq. (18) are both used to indicate the EV status that is given as

$$\text{EV status} = \begin{cases} \text{Disabled,} & \text{if } \alpha = 0, \beta = \forall \\ \text{Charging,} & \text{if } \alpha = 1, \beta = 1 \\ \text{Discharging,} & \text{if } \alpha = 1, \beta = 0. \end{cases}$$

Furthermore, $P_{k,t}^{\text{HA}}$ in Eq. (18) denotes the load of electrical appliances consisting of CS load $P_{k,t,j}^{\text{CS}}$ and FS load $P_{k,t,j}^{\text{FS}}$ at time t, where j and i represent the index of the appliances. The ε parameter indicates the scheduling priorities of the scheduled appliances, which is similar to Eq. (3). Besides, the maximum power rate of an individual household $P_{k,\max}^{\text{grid}}$ and the maximum power rate of the network $P_{\max}^{\text{grid}}$ are proposed in Eqs. (19) and (20), respectively, to limit the real-time load for the safety consideration.

3.2.2 EV-assisted NES model

In a residential community, different classes of customers exist. It is not possible for every household to purchase an EV. Thus, it is assumed that only a part of houses are installed with EV and indexed as $\hat{k}$, and the rest houses without EV are indexed as $\tilde{k}$. Similar to the EV-APS model, we define $W_{\hat{k}}^{\text{EV},(1)}$ and $W_{\hat{k}}^{\text{EV},(2)}$ as the initial energy within the k^{th} EV battery when EV leaves home of the first day and second day, respectively. Variable $W_{\hat{k}}^{\text{EV,rem}}$ represents the remaining energy within the k^{th} EV. The energy cost of the k^{th} EV on the daily trip is proposed as $W_{\hat{k}}^{\text{EV,trip}}$. Additionally, $D_{\hat{k}}^{\text{trip}}$ and $D_{\hat{k}}^{\max}$ are proposed to indicate the actual travel distance of vehicle and the maximum travel distance with a fully charged EV. Moreover, the energy charging to EV and discharging from EV are assumed as $W_{\hat{k}}^{\text{EV,c}}$ and $W_{\hat{k}}^{\text{EV,d}}$, respectively. Afterwards, the EV balance model with the relevant constraints for the k^{th} EV household can be proposed as follows:

$$W_{\hat{k}}^{\text{EV,rem}} = W_{\hat{k}}^{\text{EV},(1)} - W_{\hat{k}}^{\text{EV,trip}} \tag{22}$$

$$W_{\hat{k}}^{\text{EV,trip}} = \frac{D_{\hat{k}}^{\text{trip}}}{D_{\hat{k}}^{\max}} \cdot W_{\hat{k}}^{\text{EV,max}} \tag{23}$$

$$W_{\hat{k}}^{\text{EV},(2)} = W_{\hat{k}}^{\text{EV,rem}} + W_{\hat{k}}^{\text{EV,c}} - W_{\hat{k}}^{\text{EV,d}} \tag{24}$$

Subject to

$$\forall t,\ W_{\hat{k}}^{\text{EV,min}} \le W_{\hat{k}}^{\text{EV,rem}} \le W_{\hat{k}}^{\text{EV,max}} \tag{25}$$

$$\tau \cdot W_{\hat{k}}^{\text{EV,max}} \le W_{\hat{k}}^{\text{EV},(1)} \approx W_{\hat{k}}^{\text{EV},(2)} \le W_{\hat{k}}^{\text{EV,max}} \tag{26}$$

where variables $W_{\hat{k}}^{\text{EV,min}}$ and $W_{\hat{k}}^{\text{EV,max}}$ in Eq. (25) represent the minimum and the maximum allowed EV battery capacity, respectively. However, constraint in Eq. (26) is proposed to ensure the EV leaves home with an appropriate energy storage level, where τ is a threshold parameter.

Moreover, considering the power impact in the multi-household network, $P_{\hat{k},t}^{\text{EV,c}}$, $P_{\hat{k},t}^{\text{EV,d,v2h}}$, and $P_{\hat{k},t}^{\text{EV,d,v2n}}$ are utilized to describe the power rates of EV charging, EV discharging via V2H, and EV discharging via V2N at time t, respectively. Therefore, $W_{\hat{k}}^{\text{EV,c}}$ and $W_{\hat{k}}^{\text{EV,d}}$ in Eq. (24) can be extended as

$$W_{\hat{k}}^{\text{EV,c}} = \eta_{\hat{k}}^{\text{c}} \cdot \left\{ \sum_{l=1}^{L} \int_{T_{\hat{k},l}^{\text{c},1}}^{T_{\hat{k},l}^{\text{c},2}} P_{\hat{k},t}^{\text{EV,c}} \cdot d(t) \right\} \tag{27}$$

$$W_{\hat{k}}^{\mathrm{EV,\,d}} = \frac{1}{\eta_{\hat{k}}^{\mathrm{d,\,v2h}}} \cdot \left\{ \sum_{m=1}^{M} \int_{T_{\hat{k},m}^{\mathrm{d},1}}^{T_{\hat{k},m}^{\mathrm{d},2}} P_{\hat{k},t}^{\mathrm{EV,\,d,\,v2h}} \cdot d(t) \right\} + \frac{1}{\eta_{\hat{k}}^{\mathrm{d,\,v2n}}} \cdot \left\{ \sum_{n=1}^{N} \int_{T_{\hat{k},n}^{\mathrm{d},1}}^{T_{\hat{k},n}^{\mathrm{d},2}} P_{\hat{k},t}^{\mathrm{EV,\,d,\,v2n}} \cdot d(t) \right\} \tag{28}$$

Subject to

$$\eta_{\hat{k}}^{\mathrm{c}}, \eta_{\hat{k}}^{\mathrm{d,\,v2h}} \text{ and } \eta_{\hat{k}}^{\mathrm{d,\,v2n}} \in (0,1) \tag{29}$$

$$\forall t \in \left[T_{\hat{k},m}^{\mathrm{d},1}, T_{\hat{k},m}^{\mathrm{d},2}\right], P_{\hat{k},t}^{\mathrm{EV,\,d,\,v2h}} \le P_{\hat{k}}^{\mathrm{EV,\,rated}}, P_{\hat{k},t}^{\mathrm{EV,\,d,\,v2h}} \le P_{\hat{k},t}^{\mathrm{act}} \tag{30}$$

$$\forall t \in \left[T_{\hat{k}}, n^{\mathrm{d},1}, T_{\hat{k}}, n^{\mathrm{d},2}\right], P_{\hat{k},t}^{\mathrm{EV,\,d,\,v2n}} \le P_{\hat{k}}^{\mathrm{EV,\,rated}}, P_{\hat{k},t}^{\mathrm{EV,\,d,\,v2n}} \le P_{\tilde{k},t}^{\mathrm{act}} \tag{31}$$

$$\varnothing = \forall\left[T_{\hat{k},l}^{\mathrm{c},1}, T_{\hat{k},l}^{\mathrm{c},2}\right] \cap \forall\left\{\left[T_{\hat{k},m}^{\mathrm{d},1}, T_{\hat{k},m}^{\mathrm{d},2}\right] \cup \left[T_{\hat{k},n}^{\mathrm{d},1}, T_{\hat{k},n}^{\mathrm{d},2}\right]\right\} \tag{32}$$

where $\eta_{\hat{k}}^{\mathrm{c}}$, $\eta_{\hat{k}}^{\mathrm{d,\,v2h}}$, and $\eta_{\hat{k}}^{\mathrm{d,\,v2n}}$ denote the efficiencies of the corresponding EV behaviors. Since the EV behaviors are discontinuous and may execute at different periods, different time labels are proposed. For example, time parameters $T_{\hat{k},l}^{\mathrm{c},1}$ and $T_{\hat{k},l}^{\mathrm{c},2}$ in Eq. (26) represent the start time and the end time of l^{th} charging period. The definitions of the time parameters in EV discharging periods as shown in Eq. (27) are similar to Eq. (26).

Furthermore, the discharging power via V2H connection ($P_{\hat{k},t}^{\mathrm{EV,\,d,\,v2h}}$) cannot exceed the rated power ($P_{\hat{k}}^{\mathrm{EV,\,rated}}$) nor the actual power required of the household ($P_{\hat{k},t}^{\mathrm{act}}$) as shown in Eq. (30). Constraint in Eq. (31) is similar to (30), which limits the discharging power via V2H connection ($P_{\hat{k},t}^{\mathrm{EV,\,d,\,v2n}}$). Variable $P_{\tilde{k},t}^{\mathrm{act}}$ in Eq. (31) represents the actual load demand of the neighbor which receives the power assistance from the EV household via V2N connection. Besides, as shown in Eq. (32), the EV charging and discharging are not allowed to operate simultaneously as well for the purpose of protecting the EV battery from damage.

3.2.3 Energy trading model in neighborhood

The proposed EV-assisted NES model ensures the energy trading in neighborhood via V2H and V2N connections. However, it is necessary to declare the trading policy in neighborhood in advance, which is illustrated as follows:

1. The EV energy will be provided in priority to satisfy the load demand of the household which owns the EV.

2. After (1), the surplus EV energy will be used in priority to supply the households which are not equipped with any energy storage units (e.g., EVs.).

3. If multiple EVs have surplus energy, the EV with the most energy reserve will be adopted in priority to assist neighbors' load demand.

4. If multiple households require energy assistance, the household which requires more load demand during high-price period will receive the energy sharing in

priority, and each house can obtain energy assistance from only one EV energy provider.

5. The allocation of the EV energy will follow the principle of maximizing the benefits of the EV provider.

In addition to these, $B_{\hat{k}}^{\mathrm{NES}}$ and $B_{\tilde{k}}^{\mathrm{NES}}$ are proposed to describe the obtained benefit of the households who sold EV energy and received energy assistance, respectively, via NES model. Hence, $B_{\hat{k}}^{\mathrm{NES}}$ and $B_{\tilde{k}}^{\mathrm{NES}}$ can be formulated as follows:

$$B_{\hat{k}}^{\mathrm{NES}} = \theta\% \cdot \left(C_{\tilde{k}}^{\mathrm{dmd}} - C_{\hat{k}}^{\mathrm{EV,\,c}}\right) \tag{33}$$

$$B_{\tilde{k}}^{\mathrm{NES}} = (1-\theta\%) \cdot \left(C_{\tilde{k}}^{\mathrm{dmd}} - C_{\hat{k}}^{\mathrm{EV,\,c}}\right) \tag{34}$$

Subject to

$$C_{\tilde{k}}^{\mathrm{dmd}} - C_{\hat{k}}^{\mathrm{EV,\,c}} > 0 \tag{35}$$

where θ is a profit distribution parameter and normally $\theta\% = 0.5$, which means the participants in energy trading share the profits equally. Additionally, $C_{\tilde{k}}^{\mathrm{dmd}}$ is the cost for electricity demand without EV sharing within household without EV equipment, and $C_{\hat{k}}^{\mathrm{EV,\,c}}$ is the cost for EV charging of the energy sharing part. However, the energy transaction via NES model occurs only when it is profitable as shown in Eq. (35). Obviously, this type of EV-based energy sharing model is benefit for the trading participants on both sides.

3.3 Problem formulation and optimization

The objective of this work is to minimize the total daily cost for energy usage of the residential network with K households as well as shape the load to a proper level in peak demand time. To begin with, the day is split into equal time divisions with a time interval and indexed as t. The total cost function is given in Eq. (35):

$$\mathrm{Min\ TC} = \sum_{k=1}^{K} \left\{ \sum_{t=1}^{24} \left(R_t \cdot W_{k,t}^{\mathrm{grid}}\right) - B_k^{\mathrm{NES}} \right\} \tag{36}$$

where R_t is the dynamic electricity pricing, $W_{k,t}^{\mathrm{grid}}$ is the energy consumed on the grid of the k^{th} household, and B_k^{NES} represents the cost benefit that the householder can obtain in energy trading in neighborhood by using the proposed NES model.

According to the defined trading policies between neighbors, in order to minimize TC, we have to minimize each TC_k which denotes the total cost of the k^{th} household in the network. Therefore, the objective function can be formulated as

$$\mathrm{Min\ TC} = \sum_{k=1}^{K} \mathrm{Min}\left\{\mathrm{TC}_k\right\} = \sum_{k=1}^{K} \left\{ \mathrm{Min}\left\{ \sum_{t=1}^{24} \left(R_t \cdot W_{k,t}^{\mathrm{grid}}\right) \right\} - \mathrm{Max}\left\{B_k^{\mathrm{NES}}\right\} \right\} \tag{37}$$

Based on the objective function in Eq. (36), the optimization process can be executed in two stages. First, it minimizes the total cost for electricity bill by optimally allocating the EV energy via V2H connection. Second, it maximizes the benefit from energy transaction in neighborhood by optimally distributing the surplus energy via V2N connection. Based on the previous model descriptions, both optimization stages are linear problems. Therefore, the mixed-integer linear programming (MILP) which is the most appropriate technique has been used to obtain the optimal solution. However, the description of the technique is not the focus in this study, so it is not emphasized here.

Under the given models and the relevant constraints, the proposed DR strategy is able to optimally schedule appliances within the multi-household network in accordance with the comprehensive affecting factors, such as EV behaviors, user preferences, and load scheduling priorities. Here, the maintenance cost for EVs and home appliances is neglected in this work.

4. Case study and results

In order to evaluate the feasibility of the proposed DR strategies, two cases are proposed in this section. Case 1 is used to evaluate the EV-assisted DR strategy for an individual household, and Case 2 is proposed to evaluate the EV-assisted DR strategy for a multi-household network with multiple EVs.

4.1 Case 1: EV-assisted DR strategy for individual household

This subsection demonstrates how the proposed EV-APS DR strategy can be implemented at the household level to alleviate the load burden in peak demand periods and save electric bills. Some assumptions for simulations are presented.

4.1.1 Case description

In this case, the selected time interval for the optimization is set as 3 minutes (0.05 hr). The households comprise over 15 types of commonly used loads covering both CS and FS appliances. The EV and four other commonly used appliances, hot water tank, dish machine, washer, and drying machine, are considered as the flexible loads in this study.

In addition, the ε parameters are given to indicate the priorities of the related loads. According to the user preferences, it is randomly assumed. Besides, in accordance with the operating habits, the objective scheduling time for these appliances is set randomly, such as EV charging [0:00–8:00]; hot water tank [17:00–22:00]; dish machine [18:30–24:00]; washer [17:00–24:00]; and drying machine [0:00–8:00].

Moreover, the Tesla Model S (EV) with a battery rating of 30 kWh (up to 60 kWh) is employed in the case study. It is provided with a charging wall connector (one-phase grid) limited to a charging power of 7.4 kW. The discharging power for household appliances is up to 3.0 kW as it is shown in **Table 2**. The charging and discharging efficiencies are considered as $\eta_1 = \eta_2 = 0.95$. It is also considered that the householder always arrives home at 5:00 p.m. with 18 kWh (60%) remaining energy in EV battery and leaves home at 8:00 a.m. in the next morning with fully charged battery (100 $\pm$ 5%, 30 $\pm$ 1.5 kWh). However, the minimum remaining energy in EV is restricted to 7.5 kWh (25 $\pm$ 5%) to avoid the deep discharging. The deep charging will cause damages to the battery and reduce battery life. Furthermore, the UK dynamic pricing data of a typical day which is used in this case is presented in **Figure 3**.

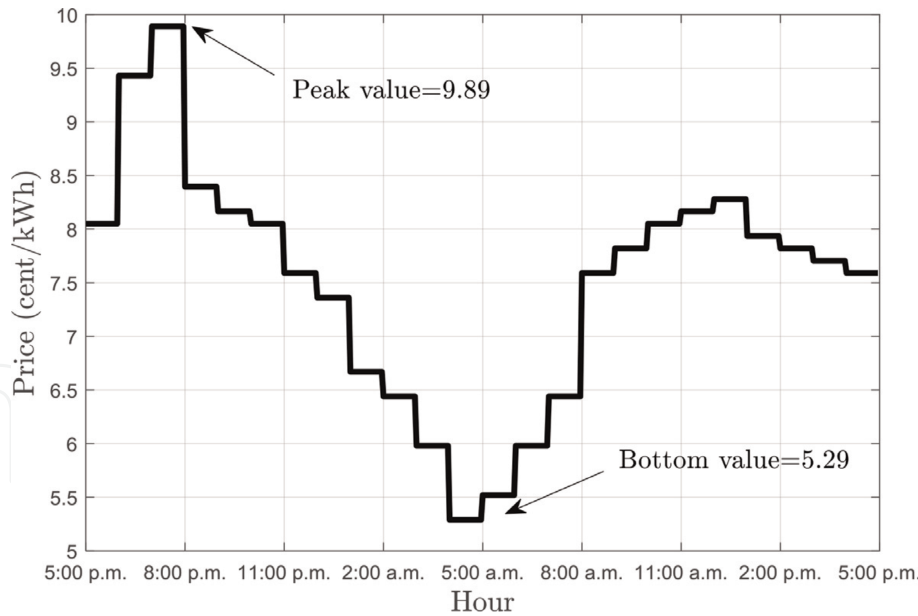


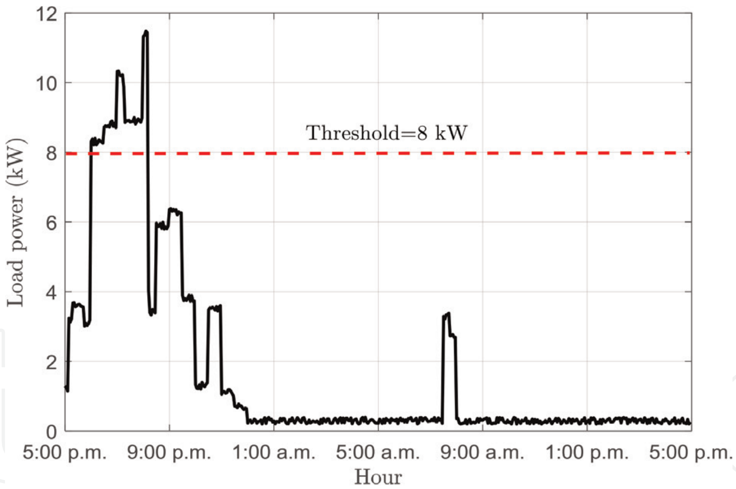
Figure 3.
UK real-time electricity pricing data.

4.1.2 Simulation result

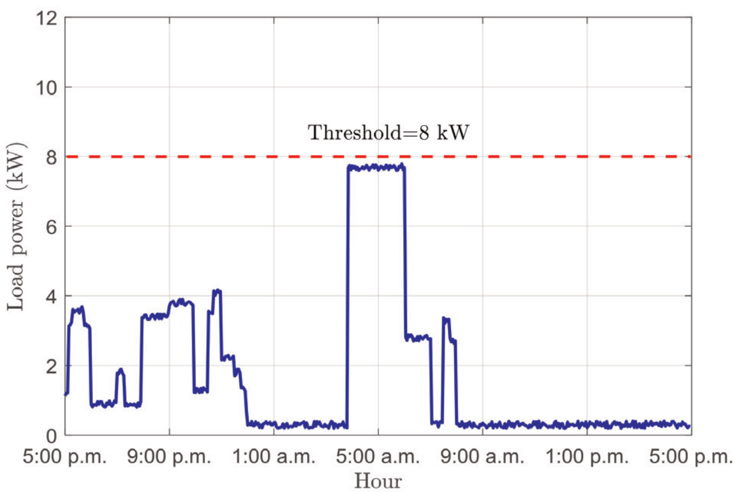
Assuming that the target household demand limits of 8 kW all day in this study, **Figure 4** presents the overall load shaping results of the household appliances. Specifically, **Figure 4(a)** shows the original load profile without DR. It can be seen that the peak demand time occurs between 6:00 p.m. and 8:10 p.m. The total house load exceeds the 8 kW limit during this period, and the maximum load demand is 11.5 kW which occurs at around 8:00 p.m. Additionally, (b) and (c) in **Figure 4** present the load profiles after scheduling by using the LSC DR strategy [20] and the proposed EV-APS DR strategy, respectively. Apparently, the load burden is alleviated, and the load decreases to an appropriate level in both (b) and (c). Nonetheless, compared with the results in (b), the load demand in (c) between 6:00 p.m. and 9:40 p.m. approaches to a very low level, since the EV discharging is activated during this time. As a consequence, the EV takes 3.2 hour to charge as it is shown in (c), which is longer than the charging time (2.1 hour) in (b).

Moreover, since the EV plays a great role in power supplying in modeling, the real-time EV remaining energy variation at household parking station by using the proposed EV-APS DR strategy is illustrated in **Figure 5**. Specifically, the EV arrives at home at 5:00 p.m. as described in the figure. Between 5:00 p.m. and 10:18 p.m., the EV discharging is activated, and a part of household appliances are continuously powered by EV until the amount of EV remaining energy reaches the minimum threshold (7.5 kWh). However, the EV is charged from 3:00 a.m. to 6:18 a.m. in the next day morning to enable the EV leaves home with the fully charged battery at 8:00 a.m. According to the results, it can be seen that the EV remaining energy variation directly corresponds with the load curve in **Figure 4(c)**, which indicates that this emulation method is correct and feasible.

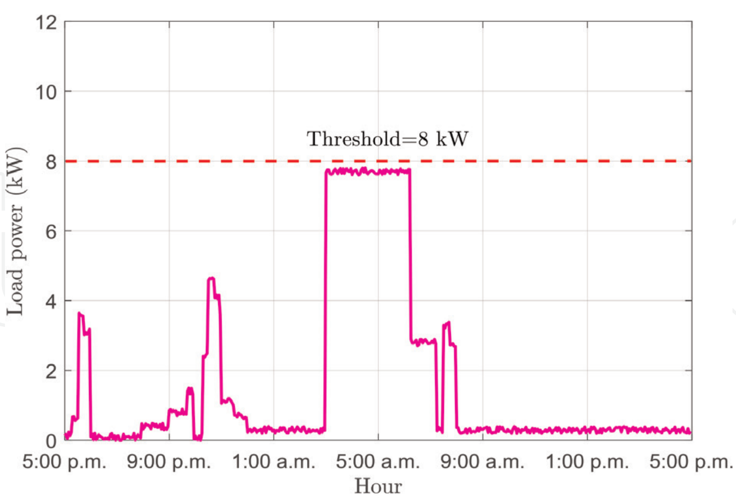
Figure 6 shows the accumulative probabilities of the reshaped load distributions by DR strategies during peak load demand period which is between 5:00 p.m. and 12:00 p.m. Based on the figure, we can see that the probabilities for the case $P^{grid} <$ 1 kW of the original load profile without DR, the LSC DR shaping profile, and the EV-APS DR shaping profile are 7.1%, 24.3% and 72.9%, respectively. For the case $P^{grid} <$ 3 kW, the probabilities are 23.6, 53.1 and 86.4%, respectively. The results indicate that the load shaping performance by the EV-APS DR strategy is the best as



(a)



(b)



(c)

Figure 4.
The overall load shaping results. The load profiles of (a) without DR, (b) by the LSC DR, and (c) by the proposed EV-APS DR.

a higher percentage load is shaped to a low level, which proves that the proposed method is an effective tool in load shaping.

The total cost is another issue that customers concern. On the basis of the DP tariff, the daily electric cost can be obtained. **Figure 7** presents the accumulative

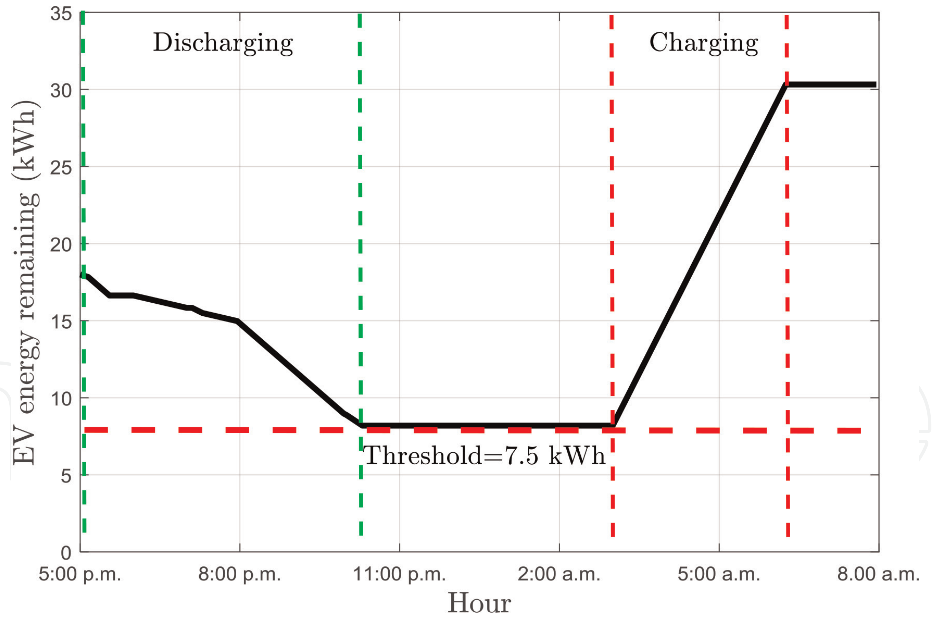


Figure 5.
The real-time EV remaining energy variation at parking station.

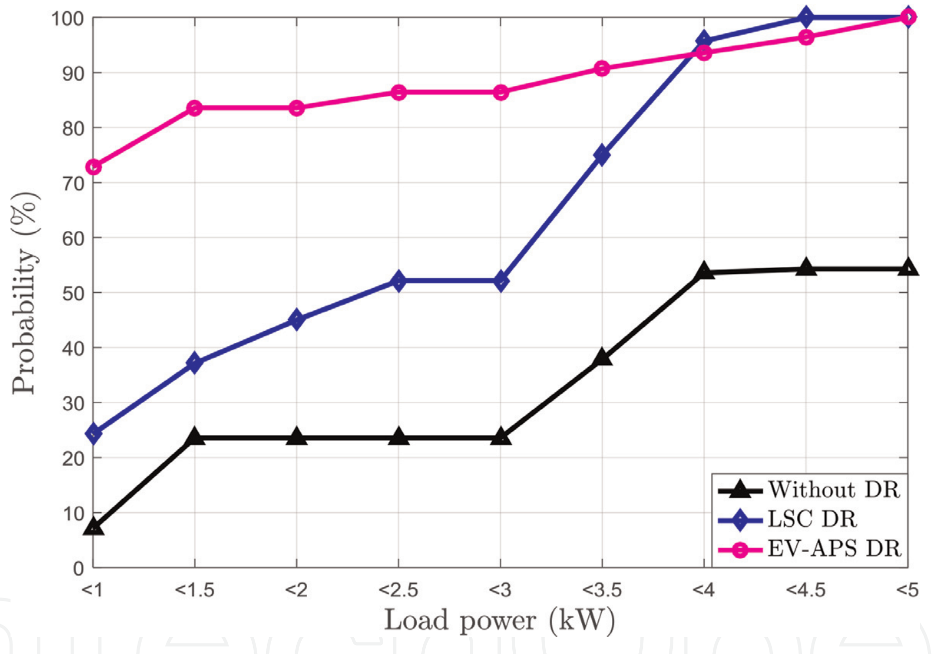


Figure 6.
The accumulative probability of the load distribution during peak load demand hours.

cost comparison between different demand response strategies. Obviously, the proposed EV-APS DR strategy performs superior than other approaches in comparison. The total electric bill of the original load demand of a typical day is about £3.6. However, it decreases to £2.9 and £2.5 by using the LSC DR and the EV-APS DR, respectively. The total saving costs are about £0.7 and £1.1, which are equivalent to 19.4 and 30.6%, respectively. Compared with the LSC DR strategy in literature, the proposed DR strategy in this paper has a better performance in load shaping and higher cost saving percentage (11.2% improved), obviously.

4.2 Case 2: EV-assisted DR strategy for multi-household network

This section proposes a case study to demonstrate how the DR strategy with the EV-assisted NES model can be implemented at the side of residential community, to

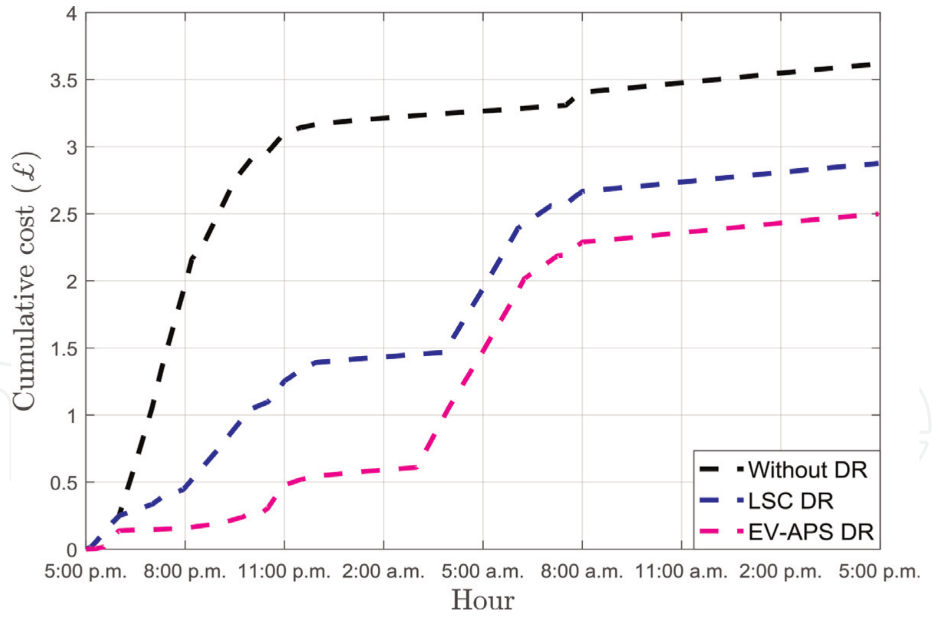


Figure 7.
The accumulative cost comparison results between DR strategies.

Parameter	House #1	House #2	House #3	House #4	House #5
EV status	Active	Active	Active	Disable	Disable
ToA (first day)	5 p.m.	6 p.m.	7 p.m.	—	—
ToL (second day)	8 a.m.	9 a.m.	10 a.m.	—	—
CR (kW)	7.5	6.5	5.5	—	—
DCR (kW)	3.5	3	2.5	—	—
ERoA (kWh)	26	24	22	—	—

Table 3.
Electrical vehicle parameter specification.

save electric bills and alleviate the load burden in peak demand time simultaneously.

4.2.1 Case description

The optimization problem for the total cost minimization is formulated as linear programming aimed to reduce the daily bill of each household as much as possible. In the case study, the selected time interval for the optimization is set as 3 minutes. The adopted multi-household network is assumed to comprise five households for convenience. For each household, over 15 types of commonly used domestic appliances covering both FS and CS appliances are accounted.

In addition, as not all the users are able to purchase an electrical vehicle, only 3/5 of the households are assumed to be equipped with EVs to support the neighbor energy sharing. For each EV device, a battery capacity of 35 kWh is employed. The charging and discharging (via V2H and V2G) efficiencies are all considered to be 0.95 for convenience. The minimum remaining energy in EV is restricted to 10% ($\tau = 0.1$) of the battery capacity to avoid the deep discharging.

Besides, the parameters about the EV status, time of arriving (ToA), time of leaving (ToL), charging rate (CR), discharging rate (DCR), and energy remaining of arriving home (ERoA) of the specific EV within each household are given in **Table 3**.

4.2.2 Simulation results

Figure 8 presents the overall load shaping results for the multi-household network by using different DR programs. It is assumed that the threshold of the overall load demand is 25 kW. Specifically, it can be seen that the LSC demand response strategy can slightly alleviate the load burden, particularly around 9 p.m. This is because limited appliances are scheduled, and none of EVs are adopted in the LSC DR program. However, the load shaping performances of using EVs without NES and EV-assisted NES in (c) and (d), respectively, are much better than the results in (a) and (b). The load demand of the entire network in both (c) and (d) has remained below the threshold apparently due to the EV discharging contributions.

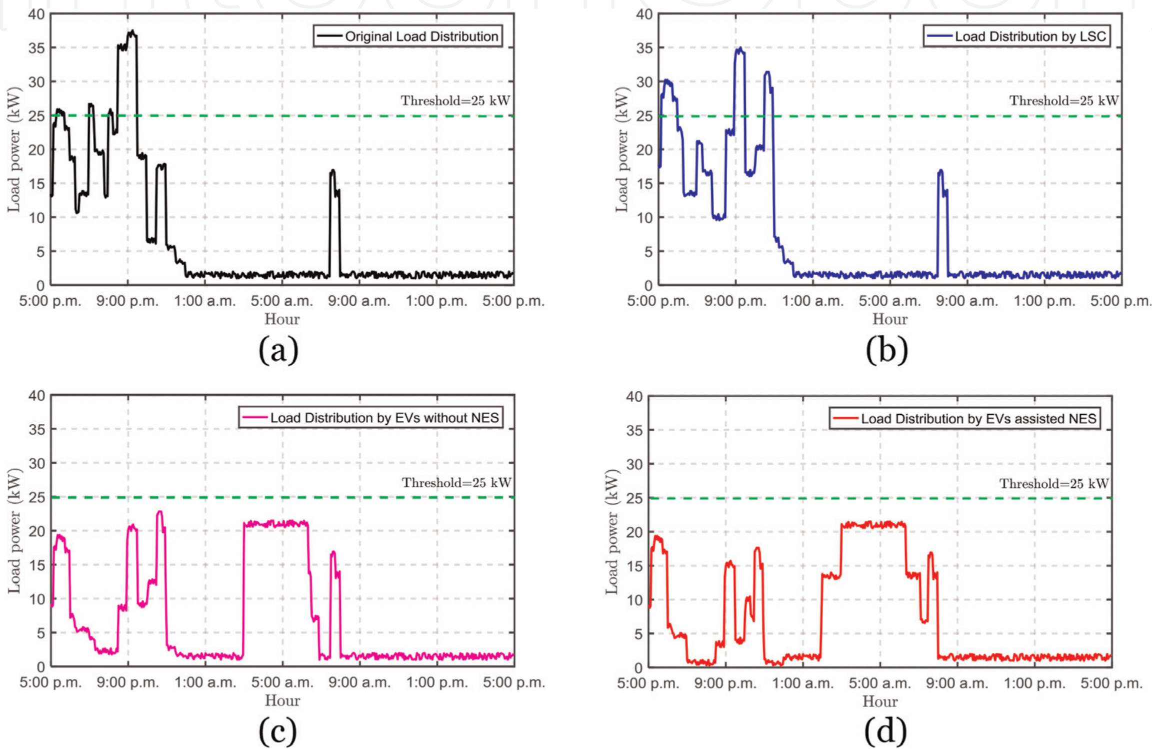


Figure 8.
Overall load shaping results for the multi-household network by using different DR programs. The load profiles of (a) without DR, (b) by LSC DR, (c) by EV without NES DR, and (d) by EV-assisted NES DR.

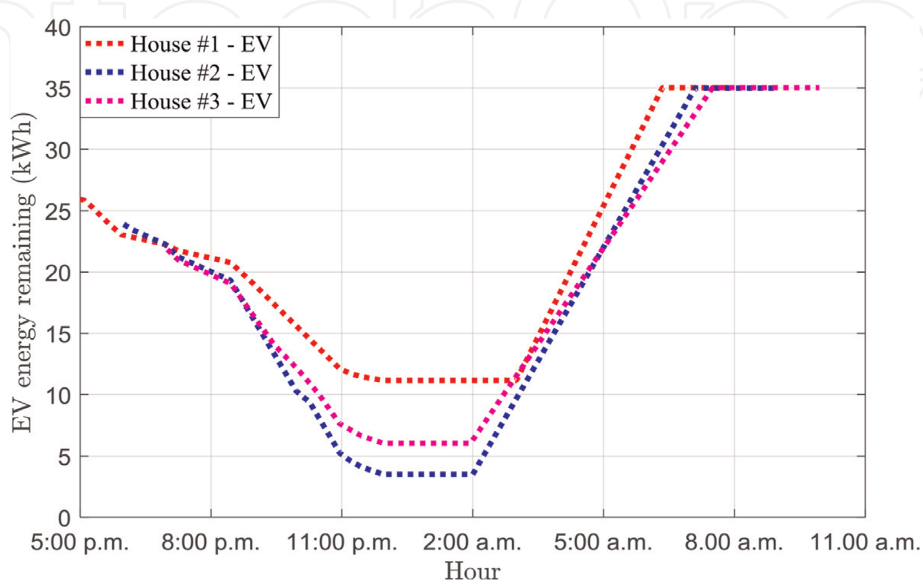


Figure 9.
Real-time energy remaining variations of EVs at parking station.

Methods	House #1	House #2	House #3	House #4	House #5
Original	3.15	3.55	3.88	2.31	2.34
LSC	3.09	3.49.	3.73	2.24	2.26
EVs without NES	1.83	2.09	2.30	—	—
EVs with NES	1.83	1.87	2.13	2.07	2.02

Table 4.
Daily cost (£) comparison by adopting different DR programs.

In addition, compared with the load distribution in (c), the load demand in (d) approaches to a lower level in peak time around 7–9 p.m. This is because the households without EVs received the energy assistance from neighbors via V2N so that the overall load demand on the grid decreases. As a consequence, it is obvious to see that the EVs take more time to charge the batteries in off-peak time for the usage of the second day. Moreover, since the EVs play a great role in power transaction within the network, the real-time energy remaining variations of EVs (#1, #2, and #3) at parking station are illustrated in **Figure 9**.

In terms of the daily electricity cost, the proposed approach can obtain more benefits compared with the literature DR programs as shown in **Table 4**. According to the cost results, apparently, the proposed DR with an EV-assisted NES model performs the best with the lowest cost in the comparison for all cases. Specifically, as house #1 does not participate in the energy trading in neighborhood due to the lower distributing priority, there is no cost difference between using EVs with and without NES. Nonetheless, as the energy providers in the transaction, the costs of house #2 and house #3 are reduced by 47.3 and 46.1%, respectively, by adopting the EV-assisted NES model compared with the original cost. Additionally, about 10.5 and 7.4% cost reduction can be achieved compared with the method of using EVs without NES. On the other side of the trading, house #4 and house #5 that are not equipped with EVs also obtain the benefits from the energy sharing. About £0.24 and £0.32 which are equivalent to 10.4% and 13.7% cost saving can be gained during the transaction for house #4 and house #5, respectively.

In overview, for this selected residential community including five individual households, the total payment saving is about £5.31 which is equivalent to 34.9% in this case. Obviously, the adopted EV-based NES model is beneficial for the energy trading participants on both sides, and significant improvements can be achieved comparing with the literature DR programs.

5. Conclusion

The aim of this work is to develop DR strategies assisted by EVs, to jointly optimize the household appliance scheduling and economic cost based on DP for different scales of households. An EV-APS-based DR strategy has been proposed first and then extended to an EV-NES model-based DR strategy. The numerical results demonstrated that for by using the EV-APS-based DR strategy for a single household, 86.4% of the load in peak hours can be shifted to an off-peak time and that the daily electric cost can be reduced by 30.6%. For the multi-household network, the load can be significantly shifted to an appropriate level, and the daily electric cost of the entire network can be reduced by 34.9%. On the basis of the achieved results, we can conclude that the proposed DR strategies in this chapter are energy-efficient solutions and can fulfill the tasks of load balancing and cost saving for the smart grid and customers simultaneously.

Acknowledgements

A part of the chapter was taken from the paper entitled "Dynamic pricing based and electric vehicle assisted demand response strategy," which has been published in 2017 IEEE International Conference on Smart Grid Communications (SmartGridComm), and we have obtained the permission to reuse it.

Conflict of interest

The authors declare that they have no conflicts of interest.

Funding

This work is partially supported by the XJTLU Research Development Fund (PGRS-13-03-06, RDF-14-03-24 and RDF-14-02-48) and AI University Research Centre (AI-URC) through XJTLU Key Program Special Fund (KSF-P-02).

Author details

Xing Luo[1,2], Xu Zhu[1,3]* and Eng Gee Lim[2]

1 Department of Electrical Engineering and Electronics, University of Liverpool, UK

2 Department of Electrical and Electronic Engineering, Xi'an Jiaotong-Liverpool University, P. R. China

3 School of Electronic and Information Engineering, Harbin Institute of Technology, Shenzhen, P. R. China

*Address all correspondence to: xuzhu@liverpool.ac.uk

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